Scaling Distributed Machine Learning with the Parameter Server

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The World We Live in Now

Real world training data sizes

1TB - 1PB

resulting in models with

10^9 - 10^{12} parameters.

The necessity of fault tolerance at scale

≈ #machine × time	# of jobs	failure rate
100 hours	13,187	7.8%
1, 000 hours	1,366	13.7%
10, 000 hours	77	24.7%

Table 1: Statistics of machine learning jobs for a three month period in a data center.

Easily accessible clouds

Goal

A distributed system supporting efficient execution of Machine Learning algorithms used daily on “trillions of trillion-length feature vectors” possibly even in real-time.

Parameter Server Architecture

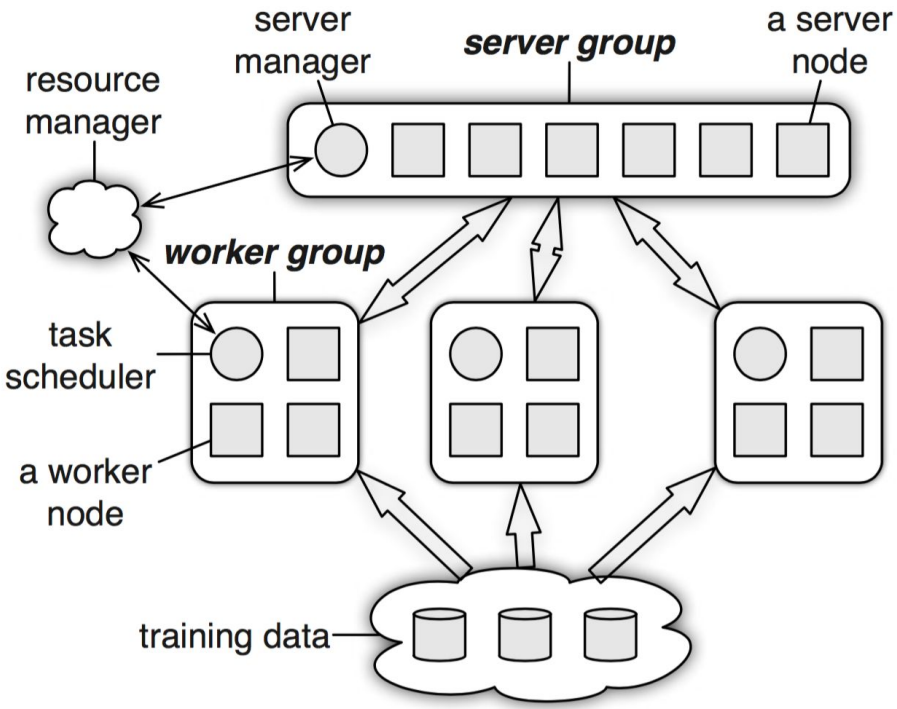


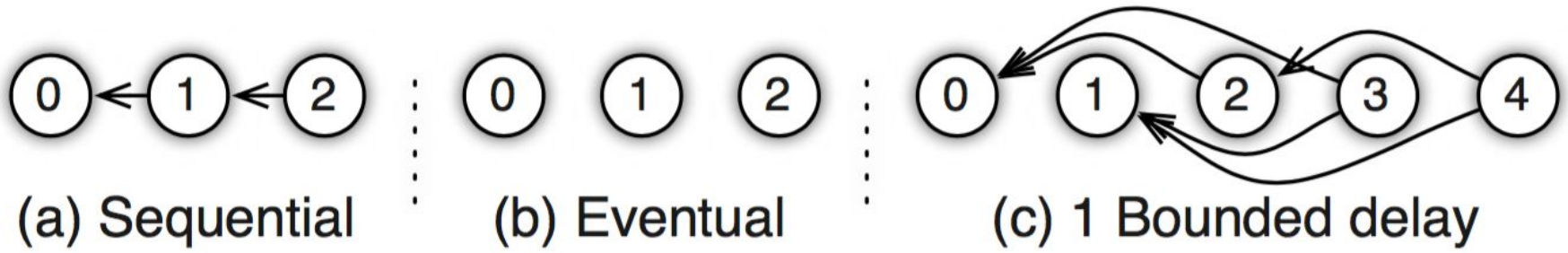
Figure 4: Architecture of a parameter server communicating with several groups of workers.

System Aspects

- Server and worker elasticity (4.5-4.6)
- (Key, Value) vector data representation (3.1)
  - with ordering for vector and matrix semantics
- Asynchronous tasks with optional user-defined dependencies (3.4)
- Range-based communication batching for efficient communication (3.2, 4.2)
- Range-based vector clocks supporting fast recovery and consistency (4.1)
- Fault tolerance via replication optimized with aggregation (4.4)
- Flexible consistency (3.5)

Flexible Consistency

Key insight: there's a trade-off between system efficiency and algorithm convergence rate



Tasks can start only after previous ones have finished

t = 0

All tasks can run simultaneously. The system becomes consistent *eventually.*

t = infinity

A maximal delay time (or number of iterations) *t* is set such that, any new task blocks until all the tasks *t* timesteps ago have completed.

Sparse Logistic Regression Results

- System A and System B are special purpose systems “developed by a large [unnamed] internet company”.
- A and B are > 10k lines of code
- Parameter Server requires 300 lines of code for the same functionality as B

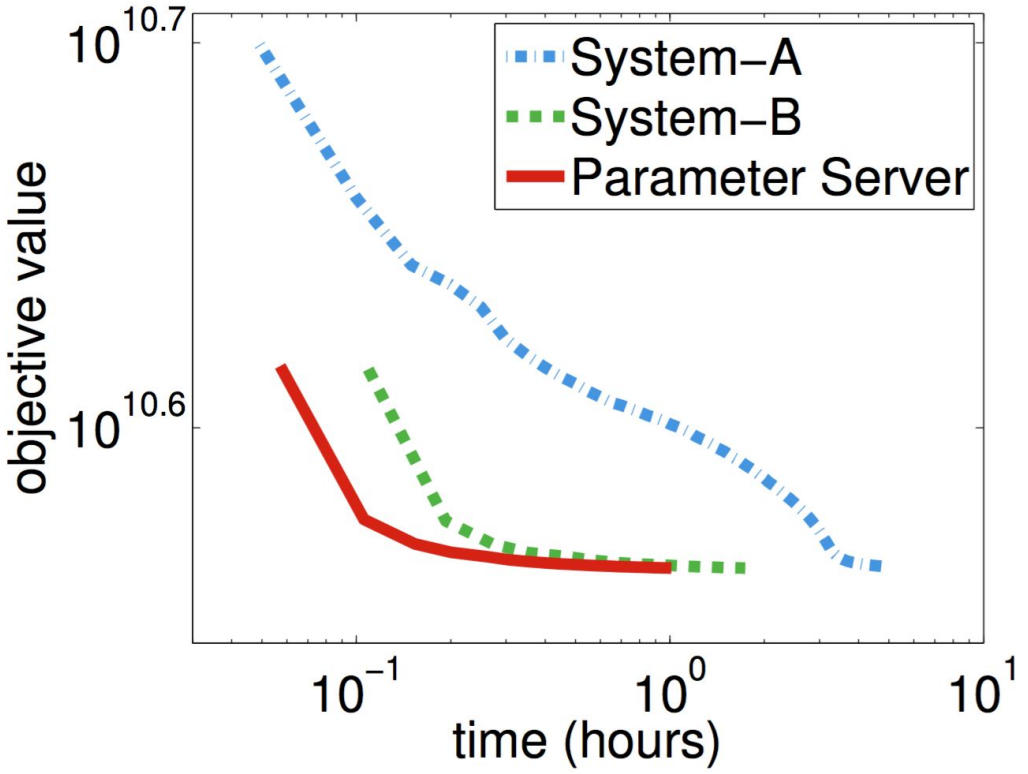


Figure 9: Convergence of sparse logistic regression. The goal is to minimize the objective rapidly.

Sparse Logistic Regression Results Continued

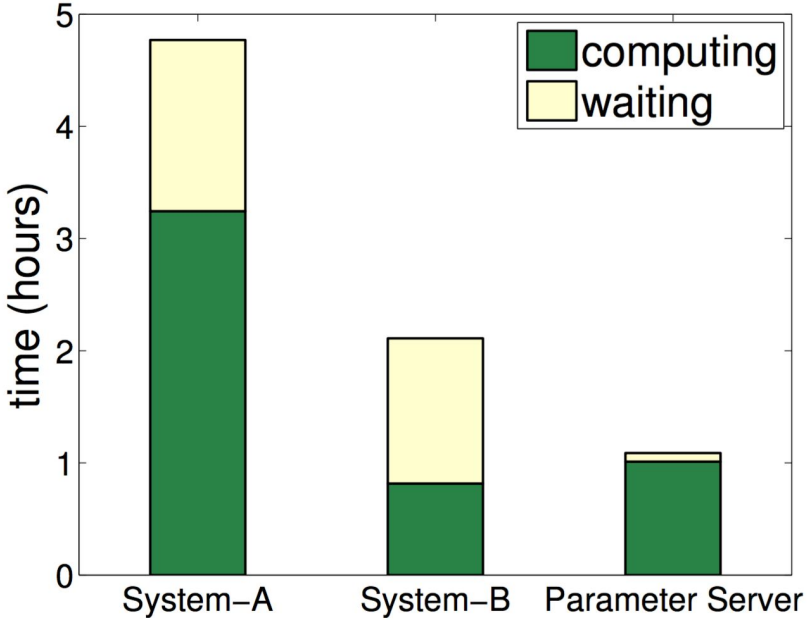


Figure 10: Time per worker spent on computation and waiting during sparse logistic regression.

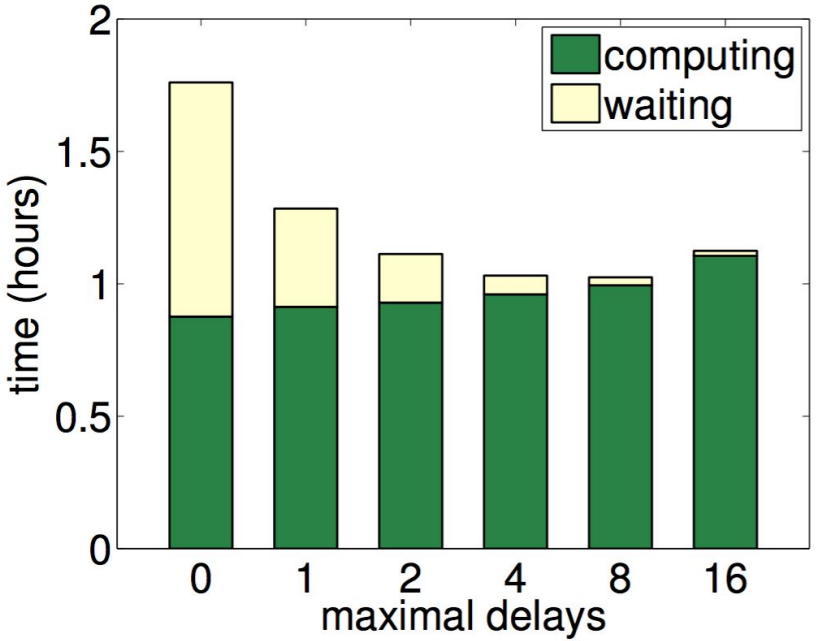


Figure 13: Time a worker spent to achieve the same convergence criteria by different maximal delays.

Other Results

- Latent Dirichlet Allocation (LDA)
  - (nothing surprising)
  - handles more data than any other LDA system the authors are aware of
  - they show scaling speeds up convergence
  - and the importance of coping with stragglers and fault tolerance
- Sketches for generality evaluation
  - performs bulk communication with compressed messages
  - peak and average operations per second and time to recover failed node measured
  - impressive numbers (other systems for comparison not included)

Peak inserts per second	1.3 billion
Average inserts per second	1.1 billion
Peak net bandwidth per machine	4.37 GBit/s
Time to recover a failed node	0.8 second

Table 5: Results of distributed CountMin

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Resulting Design Summary

- asynchronous **communication** with batching, exploiting ML algorithm design
- fast (< 1s) non-disruptive recovery **fault tolerance**
  - with vector clocks ensuring well-defined behavior
- various levels of **consistency** from which the algorithm designer can choose
- vector and matrix global parameter representation to support **ease-of-use** for ML application development
- non-restarting elastic **scalability**
- **generality** across “the most popular” machine learning algorithms